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Using Remote Sensing and Spatial Models to Monitor Snow Depth and Snow Water Equivalent

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3.1 Introduction

Snow cover is an important hydrological parameter in the global water cycle. By influencing directly the dynamics of the global water cycle, snow cover has an important control on climate through its effect on energy budgets at the surface and lower atmospheric levels (Cohen, 1994). Therefore, for climate change studies, our ability to estimate global coverage and volumetric storage of water in seasonal and permanent snow packs impacts directly on the ability to predict changes in climate from year to year and over longer periods. At a more local scale it affects the ability to budget effectively for water supply. With the continued growth in both direct and indirect evidence of climate change, plus the increasing stresses placed on the water cycle by climate change, there is a pressing need to quantify accurately at different space and time scales, the various components of the hydrological cycle.

Earth observation has been used to monitor continental scale seasonal snow cover area for 25 years and much of this effort has focused on the use of visible and infrared sensors (e.g. Hall *et al.*, 2002a). Research suggests that snow cover extent in the Northern Hemisphere has decreased by 10% since 1966 when visible/infrared sensors were first available for use (Robinson, 1999). However, little information is available on changes of snow water equivalent (SWE) at hemispheric scale over a similar time period. The instruments capable of estimating SWE have been available for a shorter period and, more importantly, the methodologies available to estimate successfully global SWE are still in an evolutionary phase. Therefore, in hydroclimatology and climate change studies, the representation of

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snow is often parameterized implicitly in climate models, perhaps as a sub-component of the model, and often at very coarse spatial scales (Foster *et al.*, 1996) that generalize SWE characteristics at grid scales of several degrees latitude/longitude in size. Satellite passive microwave estimates of snow have spatial resolutions an order of magnitude better than this. Therefore, there is an increasing need to refine methods that can provide an accurate estimation of global SWE from passive microwave sensors at spatial scales that reflect snow spatial distribution characteristics better.

Regionally calibrated approaches to SWE and snow depth estimation have been shown to work reasonably well in relatively homogeneous snow-covered areas where terrain effects are well understood (Tait, 1997; Goodison and Walker, 1994). However, in general, there is some doubt whether single regional approaches are applicable at the global scale where snow pack, land cover and terrain characteristics are more heterogeneous in nature. Thus, while the development of SWE and snow depth estimation methods has advanced in the regional domain, improvements at the global scale to estimate SWE or snow depth have been slower. Furthermore, where global studies have sought to estimate global snow volume (e.g. Chang *et al.*, 1987), the approach taken often has been static and formulated using 'average' seasonal snow pack conditions at parameterization. While these global approaches yield reasonable snow volume retrievals when integrated over large spatial and seasonal scales, local/regional instantaneous estimates can be subject to 30–50% errors or more (Hallikainen and Jolma, 1992), although there is large uncertainty associated with these errors. Nevertheless, the predicted errors are large, even for climate model inputs, suggesting that snow volume estimates are often unreliable for catchment-based studies. It is apparent, therefore, that approaches for the estimation of snow volume from passive microwave data need to be advanced into more spatially and temporally dynamic methodologies that represent snow pack processes better and should, therefore, reduce the errors of estimates. This chapter explores the possibilities and practicalities of using hydrological models of snow pack properties and radiative transfer models of microwave emissions from snow to assist with the estimation of snow volume on a global scale. We begin by discussing the character of snow depth and SWE spatial distribution before describing the current approaches of snow volume estimation from passive microwave instruments. The issue of the determination of errors linked to snow volume estimates is also addressed towards the end of the chapter; these errors are increasingly important but probably even less straightforward to derive. The chapter then concludes with some remarks about future directions.

For clarity, in this chapter we use the term snow cover as a synonym for snow cover area extent. Mostly, however, the chapter is concerned with the estimation of SWE (mm) or snow depth (cm) per unit area. While these two are related through the snow density, they are different and can have different seasonal characteristics.

3.2 Modelling Spatial Variation of Snow Depth/SWE Using *in Situ* Snow Measurements

Walsh (1984) created a generalized map representation of the spatial distribution of global snow cover. Qualitative maps are useful for providing generalized representations of the location and climatological persistence of snow cover area. More recently, efforts are

underway to build quantitative maps of global snow cover occurrence using satellite-derived estimates of snow cover (e.g. Frei and Robinson, 1999, Hall *et al.*, 2002b). However, there is far less information available about the scale of spatial variation of snow depth or SWE. We know that snow depth or SWE varies in a snowfield for a variety of reasons (topography, vegetation, meteorology) but how can this 'spatial dependency' be defined and how might it vary through space? Field experiments that measure snow pack properties are often conducted at local scales of a few kilometres and the data are usually gridded and interpolated to produce maps of snow depth or SWE. Snow maps are then used directly in hydrological models or to test snow depth or SWE estimates from aircraft instruments. Few studies have formally quantified the spatial variability of snow depth or SWE at large regional or global scales. Brasnett (1999) used global snow depth data in the operational analysis of snow depth at the Canadian Meteorological Centre and showed how its inclusion in the analysis, through spatial interpolation, improved the overall analysis of snow. However, quantitative information about the spatial variability of these data was not reported. It is important, therefore, to determine the characteristic scales of spatial variation of snow depth or SWE in continental snow packs before we attempt to monitor snow from space.

It is known that large spatial and temporal variations exist in global and local snow cover extent and volume (Frei and Robinson, 1999) and characterization of these variations is important for effective climate prediction. Spatial scales of snow cover variation were identified by McKay and Gray (1981) who characterized snow cover distribution in terms of regional variations (up to 10^6 km²), local variations (10^2 to 10^5 km²) and micro-scale variations (10 to 10^2 km²). Regional scales of snow cover distribution are controlled by latitude, elevation and orographic effects, local-scale distributions are controlled by local topographic effects such as slope and aspect and by land cover type, and micro-scale variations tend to be influenced by local transport factors such as wind redistribution (McKay and Gray, 1981). This description provided by these authors is a good starting point for understanding the nature of SWE and snow depth variation.

Snow depth and SWE can be measured directly on the ground using measurements at a point or over a limited area of a few metres with a snow pillow. In general, point measurements of snow depth or SWE produce high quality data with small location and magnitude errors. However, the spatial representativeness of these points is uncertain at larger distance scales. The only way to attempt the characterization of snow depth or SWE spatial variability necessarily relies on point measurements, usually made at official meteorological station networks and volunteer networks. Very few datasets that characterize snow cover distribution over all spatial scales are available to confirm the McKay and Gray classification. Data tend to characterize the local to regional scales with micro-scale variability snow depth or SWE observations available only at specific locations and often over short periods of time. Figure 3.1 shows three spatial scales of operational or routine snow depth measurement networks. At each site, accumulated snow depth is measured with a graduated ruler and SWE is calculated from the measured average snow depth and snow density. If no data are recorded, generally it is assumed that there was no snow present. Figure 3.1a shows World Meteorological Organization (WMO) station sites in the Global Telecommunications System network in the northern hemisphere that reported snow depth greater than 2 cm during the 2000–2001 winter season. These data are freely available from the National Climate Data Center in the USA. The maximum spatial density of measurements is 1 site per 40 km² although the average density is 1 site per 160 000 km². Figure 3.1b shows the

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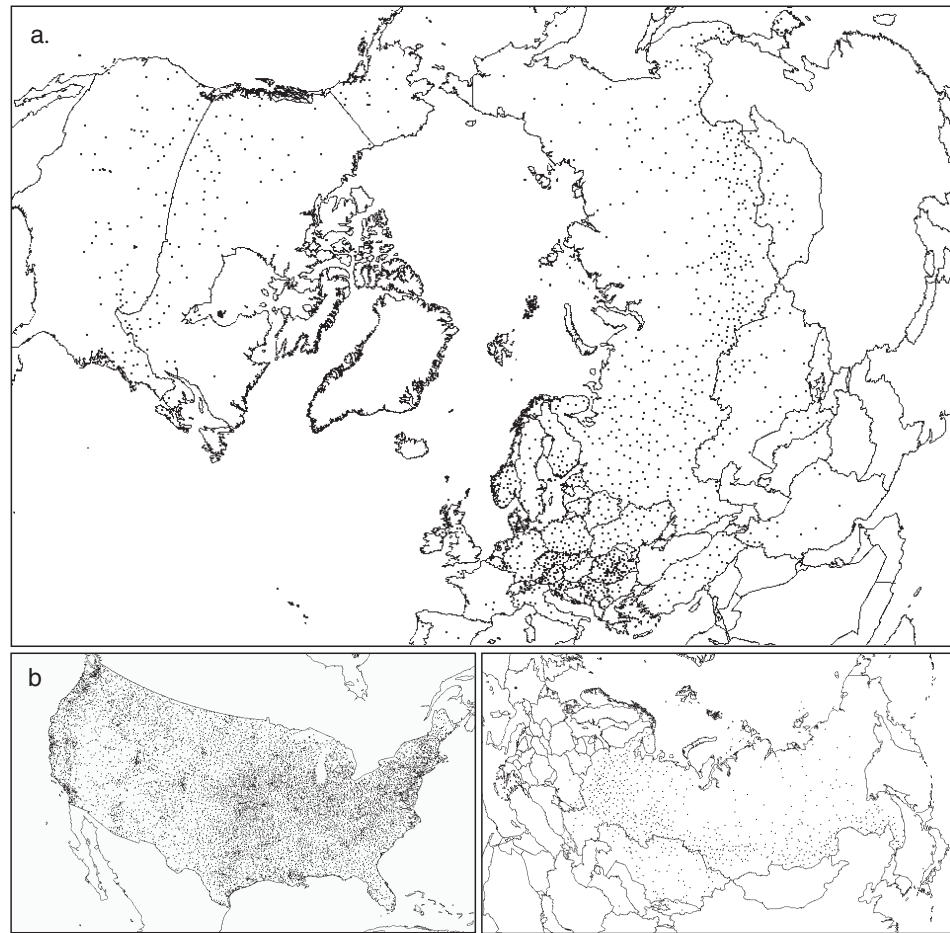


Figure 3.1 Maps of three different snow depth measurement networks: (a) represents the number of stations in the WMO GTS network on 2 February 2001 (maximum snow extent); (b) represents the total COOP station network; (c) represents the FSU network

active cooperative station network (COOP) for the contiguous states in the USA. These data are available from the National Oceanic and Atmospheric Administration and have a maximum and mean density of 1 site per 0.26 km^2 and 1 site per 1600 km^2 , respectively. Figure 3.1c shows the station locations of snow depth observations from the former Soviet Union (FSU) for 10 February, 1989. The FSU data are available from the National Snow and Ice Data Center and have a maximum and mean density of 1 site per 0.4 km^2 and 1 site per $14\,000 \text{ km}^2$, respectively. Using the average spatial densities (rather than the maxima), these area densities translate to scale lengths of 1 station per $40 \times 40 \text{ km}$, $118 \times 118 \text{ km}$ and $400 \times 400 \text{ km}$ for the USA, FSU and WMO datasets, respectively. Therefore, based on McKay and Gray's specification, potentially the datasets are the most representative at local to regional scales. (It is tempting to consider that the COOP data provide a good opportunity

to investigate highly local-scale or even micro-scale spatial variability. However, the actual number of stations regularly reporting snow depth or SWE is rather less than this average figure suggests.) To further investigate the spatial variability of snow depth or SWE, the analysis of snow depth variograms was undertaken.

Intuitively, there is an inherent spatial dependence of snow depth or SWE in a snow field because locations closer together tend to be more similar than those further apart (see Tobler's first Law of Geography). This concept can be used to encapsulate the micro-scale of SWE or snow depth variation. 'Spatial similarity' of snow depth also can be present over greater distances on account of local or regional controls on snow accumulation (in mountainous terrain or along the track of a snow storm). In other words, spatial autocorrelation of snow depth is probably present at different scales from micro-scales through to broad regional scales. Quantification of the spatial dependence of a variable may be expressed by the semi-variogram. In statistics, observations of a selected property are often modelled by a random variable and the spatial set of random variables covering the region of interest is known as a random function (Isaaks and Srivastava, 1989). In geostatistics, a sample of a spatially varying property is commonly represented as a regionalized variable, that is, as a realization of a random function. The semi-variance (γ) may be defined as half the expected squared difference between the random functions $Z(\mathbf{x})$ and $Z(\mathbf{x} + \mathbf{h})$ at a particular lag \mathbf{h} . The variogram, defined as a parameter of the random function model, is then the function that relates semi-variance to lag:

$$\gamma(\mathbf{h}) = \frac{1}{2}E[\{Z(\mathbf{x}) - Z(\mathbf{x} + \mathbf{h})\}^2] \quad (1)$$

The sample variogram $\gamma(\mathbf{h})$ can be estimated for $p(\mathbf{h})$ pairs of observations or realizations, $\{z(\mathbf{x}_l + \mathbf{h}), l = 1, 2, \dots, p(\mathbf{h})\}$ by:

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2}p(\mathbf{h}) \sum_{l=1}^{p(\mathbf{h})} \{z(\mathbf{x}_l) - z(\mathbf{x}_l + \mathbf{h})\}^2. \quad (2)$$

As Oliver (2001) states: "[the variogram] provides an unbiased description of the scale and pattern of spatial variation". It is a useful tool, therefore, for analysing the scale(s) of variation characterized by datasets of measurements of snow depth or snow water equivalent.

Variograms were calculated for measured point snow depth data (cm) for three different datasets to investigate spatial dependencies present at different sampling scales. The three dataset frameworks described in Figure 3.1 (the WMO, COOP and FSU snow depth datasets) were used to explore the characteristics of snow depth spatial variability in each dataset. Ideally, datasets containing consistent measurements of SWE should be used, but globally, they are not available routinely so snow depth records are used. Daily samples of snow depth from each dataset were selected for northern hemisphere mid-winters (early February) from the respective archives. Although the same time periods are not represented in each case, the data provide some sense of spatial variability characterized at each scale of measurement.

The point snow depth data were projected to the Equal Area Scaleable Earth Grid (EASE-grid) (Armstrong and Brodzik, 1995) and the variograms computed for 2 February, 2001 (WMO), 10 February, 1990 (FSU), 12 February, 1989 (COOP) and 12 February, 1994 (COOP). The WMO data cover the entire northern hemisphere while the FSU data cover

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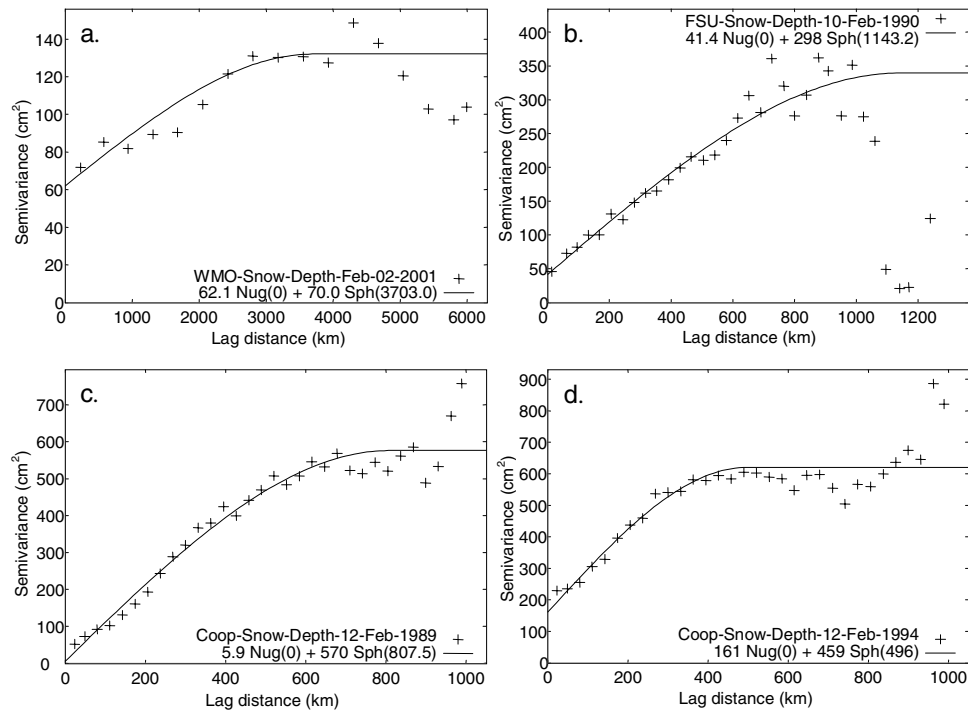


Figure 3.2 Variograms of point snow depth variation at three different scales of spatial measurement: (a) WMO GTS snow depth for 2 February, 2001; (b) FSU snow depth for 10 February, 1990; (c) COOP snow depth for 12 February, 1989; (d) COOP snow depth for 12 February, 1994

the region shown in Figure 3.1c. The COOP data were spatially cropped and only data from the upper mid-west USA, particularly from South Dakota, North Dakota and Wisconsin were used. The COOP data were refined in this manner to determine their utility for characterizing micro-scale snow depth variations. Figure 3.2 shows the four experimental variograms with spherical models fitted using the weighted least squares criterion. The lag separations chosen were the minimum distances between points in each of the datasets. The form of the variograms (in particular, that a bounded model provided a good fit in each case) suggests that a stationary random function model provides an adequate model of the variation in each case. In particular, trend models were not required. The key elements of the variogram of interest in this work are the sill, range and nugget variance. The sill variance determines the amount of variation in the variable (snow depth) and the range expresses the scale of variation in the variable. The nugget variance (intercept of the model on the ordinate) represents unresolved variation in the data that cannot be explained by the model. It can also be attributed to measurement error, or it is caused by uncertainty in estimating the variogram at short lags or uncertainty in fitting the model at short lags (Atkinson, 2001). Thus, for a well-structured variogram, at lag distances less than the range, spatial dependency is present while at lag distances greater than the range there is no spatial dependency. The reader is directed to other work (e.g. Oliver, 2001; Atkinson, 2001; Isaaks and Srivastava, 1989) that fully describes these parameters in formal and applied terms.

Figure 3.2a shows the snow depth variogram for the WMO global dataset. The average snow depth was 10 cm with a standard deviation of 10 cm. The number of snow depth reporting sites in this dataset is 1262. The range of the variogram is approximately 3700 km and the nugget and the sill variances are 62 cm^2 . There is structure evident in the experimental variogram although the nugget variance is 50% of the total sill variance suggesting that the structure is not strong. From the interpretation of the variogram of these data, spatial dependence is evident at lag distances less than 3700 km. However, at local scales of variation (less than 1000 km lag distances) the sample design cannot effectively represent the spatial variation of snow depth since the variance of the model is very similar to the nugget variance at these smaller lag distances. Thus, while interpolation of the point data is feasible given the apparent presence of spatial dependence, it should be undertaken only at grid supports of greater than $1000 \times 1000 \text{ km}^2$ (i.e., at a regional scale); the data should not be used to represent local scale snow depth variations.

Figure 3.2b, shows the modelled variogram for the FSU snow depth data. The average snow depth was 20 cm with a standard deviation of 14 cm and a population of 117 stations. The variogram structure has good definition and exhibits a reasonably well-defined sill at a range of approximately 1140 km. The nugget variance is 41 cm^2 , which although large, is much less than the sill variance suggesting that a distinct structure is present. Spatial dependence can be represented at the local scale of variation with these data since strong spatial dependence is exhibited at distances less than 1100 km. Micro-scale variations, however, are not represented by this dataset and so interpolation of the data should be restricted to grid support defined at the local scale.

For the North American COOP data, 283 stations comprised the 1989 data with a mean snow depth of 16 cm and standard deviation of 19 cm. For the 1994 data there were 281 stations with an average depth of 43 cm and a standard deviation of 23 cm. Figures 3.2c and d, representing 12 February, 1989 and 1994 data, respectively, show the variograms that exhibit perhaps the most distinct variogram structures. Clearly defined sills are present in both variograms with ranges located at approximately 807 and 496 km respectively for the 1989 and 1994 data. The sill variance for the 1989 data (Figure 3.2c) is 570 cm^2 while for the 1994 data the sill variance is 459 cm^2 . The nugget variance for the 1989 data is 6 cm, suggesting that very little measurement error affects the data at the micro-scale variation, and so reasonable representation of the data at this scale is possible. However, for the 1994 data the nugget variance is 161 cm^2 , which is larger than the 1989 data and indicates that small, micro-scale variations are less well represented by the variogram. The 1994 dataset represents effectively snow depth variability only at the local scale.

In the above examples, it is suggested that the 'standard' regional datasets are suited to the characterization of local to regional variations of snow depth (or SWE if available). While the global dataset showed some evidence of spatial variation at the regional scale, the spatial structure evident from the variogram was weak and could not be relied upon to provide a robust characterization of the spatial dependence of snow depth. At the micro-scale level of variation, the COOP and FSU data showed signs of representing snow depth variations but only when the average snow depth was shallow, when the snow depth was deeper, confidence in the representation at this scale was limited. While climate modellers are interested in snow variations at the local to regional scale, water resource managers are interested in variations at the local scale and often at the micro-scale of variation. Hence, although the 'standard' available datasets, such as those described above, might be useful

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for local scale applications, it is clear that they are not so useful for the characterization of micro-scale variations. Furthermore, the data are not available in real or even near-real time so their utility, potentially, is best suited to 'off-line' applications such as climate studies or the validation or testing of estimates of snow depth from alternative methodologies. For micro-scale applications or real or near-real time applications, the direct measurement of snow depth or SWE in these regional datasets is less useful. Instead, hydrologists should seek direct snow parameter measurements that are made at specific experimental catchments around the globe (e.g. Marks *et al.*, 2001).

3.3 Estimating Snow Depth and SWE Using Physically Based Models

The previous discussion concentrated on modelling the spatial dependency of snow depth represented by measurements made at discrete meteorological stations. The basis of the analysis is the purely spatial relationship of snow depth from one site to another. Several studies have demonstrated that other terrain and landcover parameters can be incorporated into statistical models to characterize snow depth or SWE spatial variability. For example, terrain variables (elevation, aspect, slope) or meteorological variables can be used to assist in the spatial modelling of snow depth or SWE (e.g. Kelly and Atkinson, 1999; Judson and Doeksen, 2000; Elder *et al.*, 1998; Carroll and Cressie, 1997). However, these approaches tend to represent snow depth or SWE at a discrete point or as a point process that represents a small homogeneous snow plot (e.g. 1 ha or less). The scaling up of these models to larger-scale applications is uncertain since the relationships in the models are statistically based and may or may not be applicable at larger spatial scales. To effectively scale up point snow data an understanding of the snow physical properties and the processes that govern their evolution in vertical and horizontal space is required. To achieve this understanding, ideally, spatially dense micro-scale measurements are needed that cover a reasonably wide area. While this need can be costly to implement, pre-existing catchments and experimental networks in place have led to some important developments in the field of snow hydrology modelling and its use in representing micro-scale to local scale snow processes.

Snow hydrology models tend to be predicated on energy balance dynamics and are usually driven at a point scale or plot scale by a suite of meteorological variables representative of micro-scale energy conditions. It is not the purpose here to provide a comprehensive review of snow hydrology models. Papers by Dozier (1987) and Bales and Harrington (1995) give full summary accounts of snow hydrology methodologies. A recent paper by Davis *et al.* (2001) provides an excellent summary of the issues concerning implementation and validation of snow model estimates. Using examples from the SNTHERM model (Jordan, 1991), the paper categorizes snow models into one-dimensional process models and two-/three-dimensional models. The two-dimensional spatial snow model generally is considered an implementation of the one-dimensional model applied to individual discrete spatial domains. One-dimensional models have been validated successfully using discrete measurements of bulk snow properties (such as snow depth and SWE), and also with detailed measurements of snow properties (such as snow density and temperature profiles, snow grain size and spectral reflectance). Snow models at the point process scale are mature and can represent at least snow depth and/or SWE variables very effectively.

Extension of the one-dimensional model to two or three dimensions has also progressed. Much of the development in this field has been through the use of instrumented catchments that have a high spatial density of meteorological instruments providing fine resolution inputs to energy balance models of snow. More recently, models have started to expand the scale to local and regional-sized supports and to examine ways that aggregate meteorological input influence snow distribution (e.g. Luce *et al.*, 1998). As Davis *et al.* note: “These efforts begin to provide frameworks for using ground-based observations as validating data in modelling exercises using large spatial domains” (Davis *et al.*, 2001, p. 278). Validation of the spatially distributed models requires data on snow extent, SWE, snow surface temperature, snow surface wetness and texture, all of which are measurable quantities. However, uncertainties associated with the spatial heterogeneity of these variables make the validation of distributed models a challenging task.

In summary, snow hydrology models appear to be mature in their ability to represent snow depth or SWE at micro-scales of spatial variation. Given our proven understanding of the physical processes controlling snow pack development, it seems reasonable to expect that application of these models to increasing support scales (e.g. local scales) should be possible. For local scale representation of snow depth or SWE, snow hydrology models should provide accurate and timely information where appropriate meteorological variables are collected in a timely fashion for input to the models. However, for global applications and in many regions of the world, real-time or near real-time meteorological data are not available routinely or at a frequent enough spatio-temporal resolution. Therefore, local or regional scale generalized climate model data will need to be used as input for which added uncertainty is associated (Slater *et al.*, 2000).

3.4 Remote Sensing Estimates of Snow Depth/SWE: Recent Approaches and Limits to Accuracy

Remote sensing of SWE or snow depth is possible using the detection of naturally upwelling microwave radiation from the earth’s surface. Progress in recovering snow depth or SWE from remote sensing instruments has been made through the available ‘instruments of opportunity’ such as the Scanning Multichannel Microwave Radiometer (SMMR) and the Special Sensor Microwave Imager (SSM/I). Table 3.1 gives summary information about these instruments plus the new Advanced Microwave Scanning Radiometer EOS (AMSR-E) aboard NASA’s Aqua platform. These instruments are passive microwave systems that measure naturally upwelling microwave radiation over relatively large instantaneous field of views (IFOV) (see Table 3.1 for details of the spatial resolution of different sensors). Neither SSM/I nor SMMR instruments were designed explicitly for snow studies but both have been found to be effective for snow applications (e.g. Chang *et al.*, 1987; Hallikainen and Jolma, 1992; Tait, 1997; Foster *et al.*, 1997; Armstrong and Brodzik, 2001). However, the scale of algorithm implementation has been firmly fixed at the regional to global scales of snow spatial variation.

The spatial resolution of observation for these microwave instruments varies with the electromagnetic wavelength or frequency of the observation, as summarized in Table 3.1. For the SSM/I, for example, at high frequencies (shorter wavelengths) such as 85 GHz, the spatial resolution is of the order of 13–15 km while the lower frequencies such as 19 GHz,

44 *Spatial Modelling of the Terrestrial Environment***Table 3.1** Comparison of Aqua AMSR-E (Chang and Rango, 2000), SSM/I (Hollinger *et al.*, 1990) and SMMR (Gloersen and Barath, 1977) sensor characteristics

AMSR-E	Centre frequency (GHz)	6.9	10.7	18.7	23.8	36.5	89.0
(launched 2002)	Band width (MHz)	350	100	200	400	1000	3000
	Sensitivity (K)	0.3	0.6	0.6	0.6	0.6	1.1
	IFOV (km ²)	76 × 44	49 × 28	28 × 16	31 × 18	14 × 8	6 × 4
SSM/I	Centre frequency (GHz)			19.35	22.235	37.0	85.5
(launched 1987)	Band width (MHz)			240	240	900	1400
	Sensitivity (K)			0.8	0.8	0.6	1.1
	IFOV (km ²)			69 × 43	60 × 40	37 × 29	15 × 13
SMMR	Centre frequency (GHz)	6.63	10.69	18.0	21.0	37.0	
(1979–1987)	Band width (MHz)	250	250	250	250	250	
	Sensitivity (K)	0.9	0.9	1.2	1.5	1.5	
	IFOV (km ²)	171 × 157	111 × 94	68 × 67	60 × 56	35 × 34	

the resolution is of the order of 43–69 km. The spatial scale of observation, therefore, is firmly fixed in the domain of the local to regional scale of snow variation. These IFOV dimensions, or footprints, may be considered as averaging cells in that the brightness temperature of an observation measured at the satellite is an average thermal signal for the whole area. (In fact, these spatial dimensions represent the approximate 3 dB beamwidth at the specific frequencies and do not account for side-lobe areas that also contribute to the final thermal measurement.)

Two recent papers have summarized methods to retrieve SWE or snow depth from satellite instruments (Derksen and LeDrew, 2000; König *et al.*, 2001) and only a summary is provided here. In theory, snow acts as a scatterer of upwelling microwave radiation and at certain frequencies (or wavelengths), the scattering component dominates the overall signal if the scattering of radiation is greater than the absorption of radiation by a target. When the snow is thick, the scattering is strong and can be detected at microwave frequencies greater than 25 GHz. By comparing brightness temperatures detected at the antenna at high frequencies (potentially scattering dominated) with those brightness temperatures detected at frequencies less than 25 GHz (absorption dominated), it is possible to identify scattering surfaces. Generally, the strength of scattering is proportional to the SWE and it is this relationship that forms the basis for estimating the water equivalent or thickness of a snow pack. This has been the foundation of satellite passive microwave retrievals of SWE or snow depth.

Using SSM/I or SMMR instruments, the difference between low (19 GHz) and high (37 or 85 GHz) frequency brightness temperatures can be used to detect the presence of snow. Several diagnostic tests have been developed to screen for false snow targets such as rainfall, cold deserts and frozen ground (Grody and Basist, 1996). In addition, a dataset that masks land and sea is helpful to ensure that false snow targets are identified. Furthermore, a dataset that maps the ‘climatological (im)possibility’ of snow accumulation has been assembled

by Dewey and Heim (1981, 1983). Using passive microwave data and the diagnostic tests of Grody and Basist (1996) along with the ancillary datasets that filter out regions where snow occurrence is unlikely, the presence of snow at any location in the world can be estimated. The advantage of the microwave approach is that snow can be mapped at locations where cloud cover obscures the snow, a perennial problem for visible/infrared wavelength sensors.

If snow is dry and uniform in density and stratigraphy, then detection of snow is straightforward. However, if the snow is stratigraphically complex, shallow or wet, its detection is more of a challenge. Armstrong and Brodzik (2001) showed that early season underestimation of snow cover area is a problem for passive microwave mapping. By comparing passive microwave estimates with visible/infrared global snow maps from the NOAA interactive multi-sensor snow and ice mapping system (IMS) product described by Ramsay (1998), the under-estimation was clearly evident (Hall *et al.*, 2002a). This area of under-estimation is sufficient to produce small but significant seasonal differences in snow-covered area between passive microwave and optical datasets. Figure 3.3 shows an example of this early

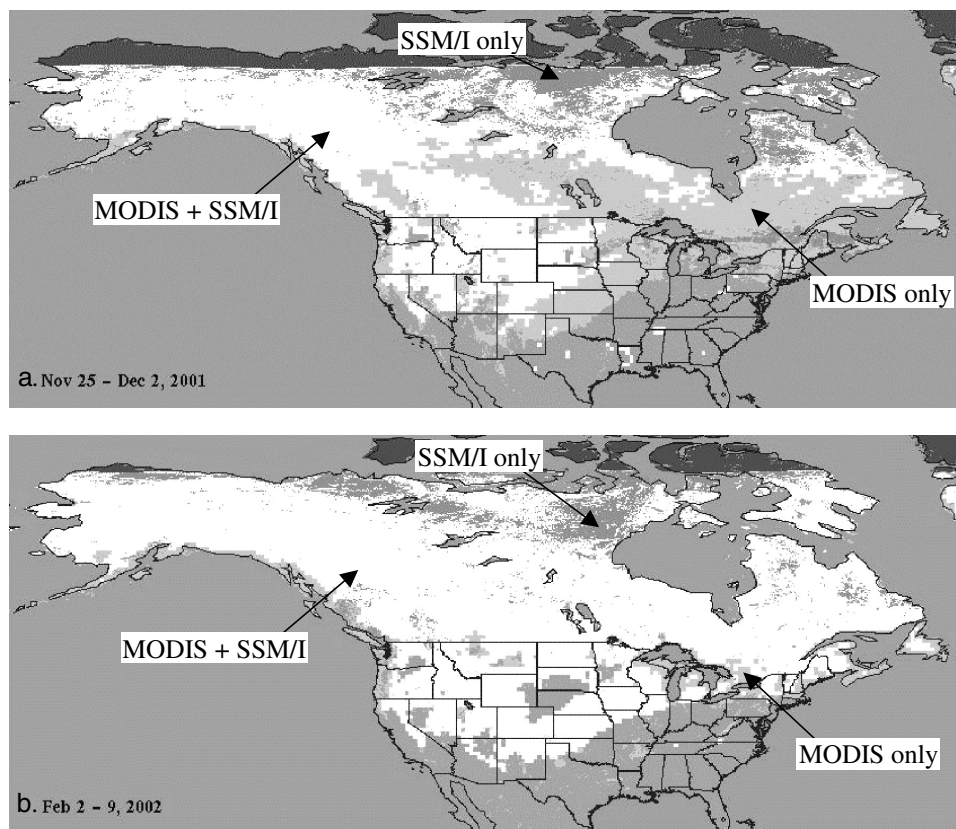


Figure 3.3 Comparison of 'static' SSM/I maximum snow area estimates and MODIS snow area estimates for 8-day periods in (a) 25 November – 2 December, 2001 and (b) 2 February – 9 February, 2002

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season discrepancy between mapping approaches for SSM/I and MODIS snow mapping products in the winter of 2001–2002. In Figure 3.3a, the early season shows significant under-estimation of the snow extent by the SSM/I data compared with the MODIS product. In Figure 3.3b, for mid-winter, the differences between estimates are smaller as the snow pack has thickened and a stronger scattering signal is observed by the SSM/I. Improvements in this mapping capability are expected with the development of the detection algorithms to AMSR-E data with its increased spatial resolution.

When snow is detected, it is necessary to estimate the SWE or snow depth and it is important to recognize that the estimation of SWE is the goal of most snow hydrological applications. This raises an important issue because the microwave response to a snow pack is sensitive to the bulk snow water equivalent. If, on the other hand, the snow pack can be characterized by a single homogeneous layer that has a constant density, the microwave response is sensitive to the snow thickness (assuming no free liquid water is present). The problem, however, is that most snow packs exhibit some form of layering so the density is variable both spatially and through time. The implication, for example, for two snow packs of identical thickness but with different stratigraphies (and bulk density) is that the microwave response will be different for each (Ulaby and Stiles, 1980). It seems reasonable to surmise, therefore, that passive microwave retrieval schemes should be focused on estimating SWE. However, the availability of reliable high quality ground-based measurements of SWE for validation is very poor, especially over large regions. Conversely, there are relatively abundant datasets of snow depth available for studies over selected larger areas. This fact produces a methodological dilemma for hydrologists: should they attempt to estimate SWE or snow depth? If they develop algorithms to estimate SWE, how are they to be validated over large regions? Alternatively, if the scientists opt to estimate snow depth, for which there are more spatially intensive datasets available, are they sacrificing estimation accuracy to estimate a variable that is only indirectly related to the microwave emission? In section 3.2 above, the average global density of snow depth recording stations was reported as 1 site per 160 000 km². Most of these WMO sites do not record SWE. The historical and regional FSU dataset reported SWE measurements routinely, but the USA COOP data consist of only snow depth. During validation of large-scale global retrieval algorithms, error metrics tend to be calculated for differences between areal microwave snow depth estimates and point snow depth estimates rather than differences in SWE since snow depth measurements have been the only potentially reliable, widespread data source available at this scale. Scientists who have chosen to estimate SWE have done so often with access to supporting SWE measurements at their scales of interest. These SWE estimation algorithms either have been developed for regional studies (e.g. Canadian prairies) or they have been developed for limited life experimental projects (e.g. BOREAS). For routine regional and global studies, these datasets are not available and so the estimation schemes tend to focus on estimating snow depth.

For satellite estimates, historically, most SWE or snow depth retrieval schemes have been based on some empirical formulation similar to the approach developed by Chang *et al.* (1987). In this approach single, homogeneous layered snow depth was expressed as a function of the horizontally polarized brightness temperature calculated from radiative transfer theory. The result of this experiment was a simple linear expression such that:

$$SD = a(\Delta TB) + b \text{ [cm]} \quad (3)$$

where SD is snow depth, b is generally regarded as zero and $a = 1.59 \text{ cm K}^{-1}$ and the assumption is made that the snow grain radius is 0.3 mm and snow density is 300 kg m^{-3} . If SWE is required in the retrieval, the units become mm and the a term is 4.8 mm K^{-1} for the same form. ΔTB represents the difference in brightness temperature between 19 GHz and 37 GHz channels at horizontal polarization or Tb_{19H} and Tb_{37H} , respectively. This model works well under simple snow conditions (single uniform layer) and where the terrain is flat and unforested. In locations where the snow physical characteristics conform to these parameter values, reasonable results are obtained, namely locations where the snow is characterized by a grain radius of 0.3 mm or bulk density of 300 kg m^{-3} . At the regional to global scale, the model parameters can be considered an average global seasonal grain size and density so at the average global seasonal scale, the results ought to be 'reasonable' (accepting that snow maps tend to underestimate). However, where these parameters are not locally representative at a given time, retrieval errors of between 10 to 40 cm snow depth or more can be expected. If hydrologists are interested in instantaneous local estimates, refinements to this approach are essential. Chang *et al.* (1996) included a forest cover compensation factor in their updated algorithm and Foster *et al.* (1997) made progress to spatially vary the coefficient a in equation (3) at broad continental scales. However, refinements are still required to reduce the errors further and improve the potentially utility of the data.

3.4.1 Spatial Representivity of SSM/I Snow Depth Estimates: An Example

To compare the spatial variability of snow depth estimates from an SSM/I algorithm with measured station snow depth, two datasets were generated consisting of global snow depth and local snow depth estimates from SSM/I data. Using the Foster *et al.* (1997) algorithm, snow depth was estimated for global snow cover on 2 February, 2001 and for the Red River catchment, located in the mid-western United States of America, for 28 January, 1994. The Red River estimates do not coincide exactly with the COOP station data for 12 February, 1994 but they are within approximately 2 weeks and it is known, from station records, that conditions did not change dramatically over this period. Assessment of the similarities in variogram structure between station data and remote sensing data should determine whether any conclusions could be drawn about the relative spatial representativity of each dataset.

Figure 3.4a and b show the variograms for the 2 February, 2001 global data and the 1994 Red River datasets respectively. In general, it is noticeable that in both cases the experimental variogram data are much smoother in character than the data for the discrete points for the same dates shown in Figure 3.2a and d. For the global data in Figure 3.4a, there is evidence of nested variation in the data, that is, variation of snow depth that occurs over different spatial scales (see Oliver, 2001, for details about nested variation). In essence, the nested variation is modelled by the variogram and produces breaks of slope at 108 km, 448 km and 1952 km. Figure 3.4a, therefore, could be decomposed into three separate variograms each having ranges of 108 km, 448 km and 1952 km relating to different scales of snow depth variation. Each variogram would represent the variation at these different spatial scales. The two smaller scales of variation (108 km and 448 km) represent local scale spatial variations of snow depth, probably caused by vegetation or topography controls. The larger-scale variation, represented by the sill with a range of 1952 km, is probably

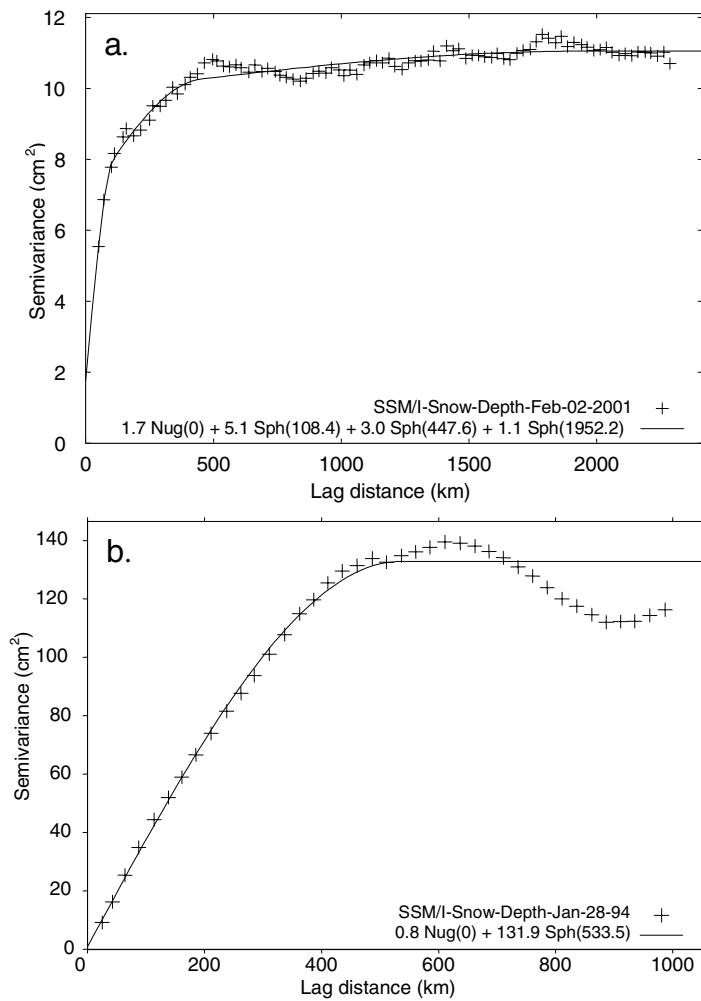
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Figure 3.4 Variograms of 'static' SSM/I snow depth estimates for (a) global snow depth on 2 February, 2001 and (b) Red River area snow depth for 28 January, 1994

caused climate controls. Thus, the variogram structure implies that an SSM/I map of snow depth for this date would contain information at the local to regional scales of variation. In addition, comparison of Figure 3.4a with Figure 3.2a shows that the spatial detail in the SSM/I estimates are finer than those found in the station data; the sampling density of the station data are not capable of resolving different scales of variability identified by McKay and Gray (1981). Furthermore, the variogram structures are quite different in character and the snow depth semivariances in the discrete data are at least an order of magnitude greater than those in the SSM/I data. This implies that the spatial variation is greater for the station data than for the remote sensing estimates, a feature that is not unexpected given the spatial smoothing implicit in the SSM/I estimates. The discrete data variogram in Figure 3.2a has

sill at a range of 3703 km but only a weak variogram structure can be discerned as noted in section 3.2. In this case study, therefore, the SSM/I snow depth estimates appear to represent more effectively and perhaps more accurately (although this cannot be stated conclusively) the spatial variability of snow depth at the global scale.

Figure 3.4b shows the variogram of snow depth for the Red River basin area for 1994. Since the COOP data are more spatially intensive than the WMO data, similarities between remote sensing and station data should be evident. In Figure 3.4b the variogram range is located at 533 km while in Figure 3.2d it is estimated at 496 km. Given the homogenous nature of the terrain in this region (Josberger and Mognard, 2002), it is suggested that little or no nested variation should be present in the variogram, which is indeed the case. For the same reason as before, a major difference between variograms is that the semivariance in the station data is four to five times greater than the semivariance in the SSM/I estimated snow depth data. At this scale of variation, the SSM/I estimates appear to be reasonable and comparable with the station data which are capable of representing snow depth variations at the given sampling spatial density.

From these two case studies, it appears that the SSM/I is capable of representing snow depth at spatial variations ranging from local scale to regional and global scales. The station data, however, are only good at representing snow depth at local scales. This is an important conclusion since it impacts directly on how global snow depth or SWE algorithms might be tested or even validated (see below). Whether or not the passive microwave estimates are 'good enough' is an issue that cannot be addressed here. All we can say is that the scale of variability appears to be reasonable based on our understanding of how snow cover varies in space. Given the local scale comparisons of SWE or snow depth based on recently developed snow depth or SWE algorithms, it is very probable that the passive microwave estimates need improvement before they are adopted by hydrologists. To begin improvement, therefore, the algorithms need to be made more dynamic and sensitive to those changing snow pack properties that affect the microwave emission signal in both in space and time.

3.5 Improving Estimates of Snow Depth/SWE at All Scales: Combining Models and Observations

It is apparent that different approaches to SWE or snow depth estimation work best at different spatial scales. While the physically based energy balance approaches are accurate at the micro-scale of variation, their performance at local to regional scales is uncertain. Remote sensing approaches, however, while not capable of producing estimates at the micro-scale, are able to estimate SWE successfully at local scales. At regional scales there is some uncertainty about their performance in general which is related to the static nature to date of the developed algorithms. To improve the SWE or snow depth estimates at regional scales, there are three possible approaches that could be taken. First, the application of snow pack energy balance models at large scales with climate models forcing as input can be developed, and second, the application of microwave remote sensing algorithms can be improved with dynamic parameterization schemes added. Third, and perhaps optimally, a combination of these two approaches can be developed and implemented. In fact, several research groups have developed retrieval schemes based on this hybrid approach with some success.

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Section 3.3 explained in general terms how physically based models operate and concluded by suggesting that they are accurate at estimating snow pack properties at micro-scales of variation. Hence, the largest improvement to algorithms that estimate SWE or snow depth at local to regional scales, is through the transformation of static methodologies into more spatially and dynamic algorithms. In other words, the algorithms need to be flexible enough to estimate snow depth or SWE from snow packs that are continually changing. Algorithm parameters require constant adjusting through the winter season to reflect these changes. One approach that can achieve this dynamism is through the use of microwave emission models that are parameterized by independently derived snow pack properties or by optimizing the match of modelled and observed brightness temperatures by adjusting the microwave emission model physical snow pack parameters.

Early theoretical studies of the microwave emission from snow used radiative transfer models with some success (see Ulaby *et al.*, 1981). Through improved understanding of the physical snow pack evolution processes, these models have developed to new levels of sophistication and accuracy in the simulation of the microwave response from snow (e.g. Tsang *et al.*, 2000; Wiesman and Mätzler, 1999). Emission models require parameter inputs describing the physical properties of a snow pack (e.g. average grain size radius, volumetric fraction of snow, vertical temperature profile) and this information can be derived from the output of an energy or mass balance model of the snow. Hence, by using the emission models in conjunction with energy or mass balance models of snow, several studies have shown demonstrable improvements in SWE or snow depth estimation accuracy. While it is not the purpose of this chapter to give detailed descriptions of these models, Figure 3.5a shows a generalized implementation approach of a coupled snow model and microwave radiative transfer model.

Weisman *et al.* (2000) coupled the microwave emission model of layered snowpacks (MEMLS) with SNTHERM and Crocus (Brun *et al.*, 1989) to estimate snow depth at an alpine site in Switzerland. Half-hourly meteorological data were collected at the site and input to SNTHERM or Crocus. These models predict a variety of snow pack properties including number of layers, thickness, temperature, density, liquid water content, and grain size and shape of each layer. These estimates are then passed to the MEMLS model which calculates brightness temperatures in the range between 5 GHz to 100 GHz at a given linear polarization and at a prescribed incidence angle. These radiative transfer calculations are based on empirically-derived scattering coefficients and physically based absorption coefficients. Results showed that the estimated brightness temperatures matched well with measurements made by ground-based radiometers nearby. Thus, the results demonstrate that our understanding of the microwave interaction processes can be translated into physical models. Chen *et al.* (2001) adopted a similar approach but this time used only the SNTHERM model and a different form of radiative transfer model, namely the dense media radiative transfer (DMRT) model based on the quasicrystalline approximation with a sticky particle model. Tsang *et al.* (2000) give a full description of this two-layer model. Compared with the MEMLS model, the DMRT has been applied to a larger area in western USA (local scale) where SNOTEL data are input into the SNTHERM model. Also, estimated emissions from the DMRT model are compared with actual SSM/I brightness temperature observations and an inversion procedure is applied to produce a final snow depth estimate. The results obtained from the approach are an improvement over static, regression-based approaches. This is especially noteworthy since the region of

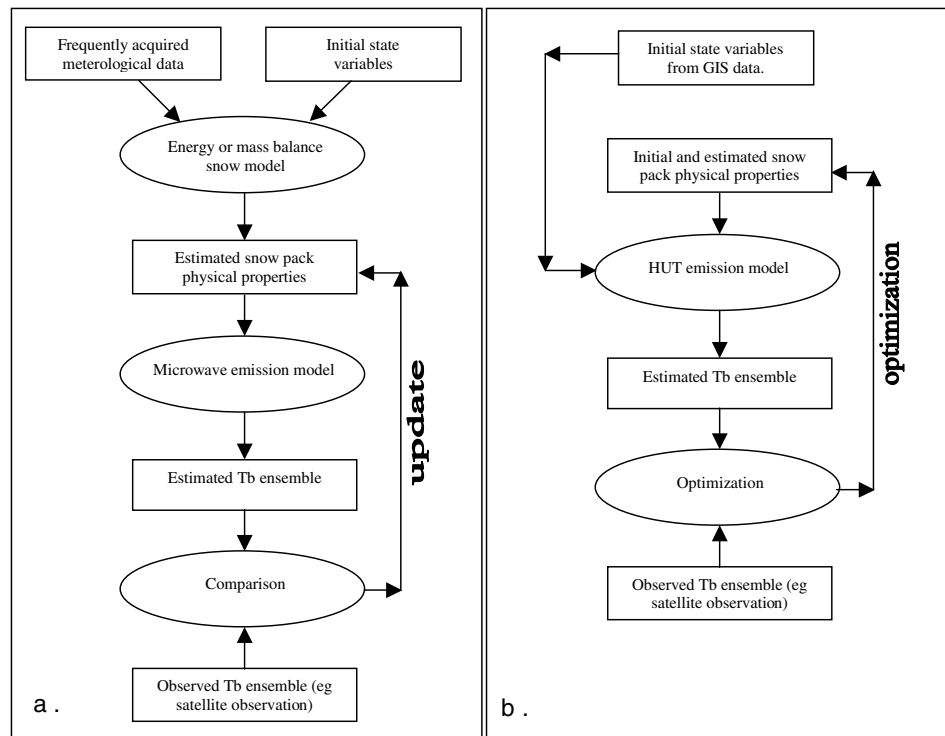


Figure 3.5 Methodological approaches to SWE or snow depth estimation using hybrid snow energy and mass balance models and microwave emission models. (a) represents the general approach adopted by Chen *et al.* (2001) (Reproduced by permission of IEEE), and (b) represents the method adopted by Pulliainen and Hallikainen (2001) (Reproduced permission of Elsevier Science). Reprinted from *Remote Sensing of Environment* 75, J. Pulliainen and M. Hallikainen, Retrieval of regional snow water equivalent from space-borne passive microwave observations, 76–85, © (2001), with permission from Elsevier

implementation is mountainous terrain where standard ‘static’ algorithms have difficulty in successful snow depth estimation. A constraint to the approach, however, is that it produces the best results for medium snow grain sizes; further refinement to the model is required if larger faceted grains develop.

The Helsinki University of Technology (HUT) snow emission model is different from the two previous models in that it is semi-empirical in approach and it does not require frequent externally derived snow state variables to estimate SWE. The model is based on radiative transfer emission from snow plus semi-empirical parameterizations of forest, atmosphere and soil (Pulliainen *et al.*, 1999). It is parameterized by geographical information (perhaps stored in a GIS) on forest stem volume, soil roughness and atmospheric optical thickness. Estimates of brightness temperature ensembles are computed at each pixel and compared with observed microwave data. An optimization routine then minimizes the error between modelled and observed brightness temperature ensembles by iteratively adjusting the snow physical properties in the model. Once the differences have been minimized, the iteration

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ceases and that SWE is the final estimate. Figure 3.5b shows a generalized diagram of the methodology. SWE retrieval errors have been found to be less than static approaches (Pulliainen and Hallikainen, 2001) with the smallest errors calculated for estimates in Finland to be 20 mm SWE.

Each of the approaches outlined above has shown improvements over static SWE or snow depth passive microwave algorithms. However, further improvement is still required as the errors are still substantial. Also, the models described so far have only been applied to local or small regional areas of interest where frequent and or high spatial resolution ancillary data are available (meteorological inputs, terrain and vegetation cover data). The challenge is to apply these methods to regions where the initialization data required for the emission model or the snow energy or mass balance models is largely non-existent or must be derived from outdated historical maps, large regional scale re-analysis or climate model data. In the case of MEMLS and the DMRT implementations, this poses a significant challenge since these models rely on frequent meteorological inputs from nearby stations for forcing SNTHERM or Crocus. For the HUT model, detailed information about stem volume is required along with atmospheric factors that are often unavailable at the scale required. Therefore, even though these hybrid approaches are improvements on the previous static algorithms, further research activity is required to enhance these models so that they can be implemented globally. Kelly *et al.* (2002) have demonstrated that a microwave emission model can be parameterized by a simple empirical model of grain growth for which grain radius is estimated from evolution through the season and the history of estimated temperature differences through the pack. It is based on the DMRT approach of Tsang *et al.* (2000) but rather than use data from meteorological stations, surface temperatures are estimated from an empirical relationship between SSM/I brightness temperatures and surface temperature. The implementation is a simplified DMRT model applied deterministically to estimate snow depth (inversion is not required). Despite its simplicity in its current form, the results so far are an improvement on those from 'static' approaches; for the 2000–2001 winter in the northern hemisphere, the simplified DMRT approach produced global seasonal estimates that were 3 cm of snow depth better than the Foster *et al.* (1997) algorithm. It is expected therefore that for this global algorithm, and the HUT and DMRT implementations, estimates of snow depth or SWE will improve as parameterization and initialization datasets improve. Additionally, with radiometrically enhanced passive microwave instrument technology such as AMSR-E, the errors will be reduced even further.

3.6 Conclusion

In this chapter, we have examined the way in which (spatial) models are used in the estimation of snow cover and especially snow depth or SWE. The variogram analysis suggested that for point measurements of snow depth at meteorological stations, only local-scale networks, where the station network is sufficiently dense (less than 1 per 40 km × 40 km area in the case of the COOP network), can quantify the spatial variability of snow depth. In regions where the cover is sparse, the representativeness of point data is uncertain and should not be relied on to characterize the spatial variability of snow depth. In the case of spatial estimates of snow depth or SWE, micro-scale variations are

successfully represented by physically based models, which are dynamic in operation and can estimate suites of snow hydrological parameters. At the local scale of variation, these physically based models can also be used to estimate the changing SWE or snow depth of a pack provided sufficient meteorological data inputs are available. As the area scales to the regional domain, it is uncertain whether these models can be used successfully to represent snow depth or SWE variability. Remote sensing retrievals, on the other hand, are well suited to local to regional scale applications as demonstrated by the structure in the variograms of snow depth estimates in Figure 3.4. However, the errors produced are still large and need reduction before these estimates are adopted more generally. It seems that a promising area of research in the form of hybrid physically based models and microwave emission models should improve our estimates of SWE and snow depth at regional and global scales. This is an interesting prospect since traditionally, snow mass or energy balance models have been subordinated by remote sensing application scientists or vice versa. Davis *et al.* contend that “Ironically, we may soon see the use of high resolution, process-detailed snow models to aid in interpolating ground measurements for validating remote sensing algorithms to recover SWE” (2001, p. 283). Given the nature of snow depth or SWE spatial variability, this seems entirely reasonable. If snow hydrology models are capable of estimating SWE at finer local scales, then it makes sense for passive microwave estimates to be tested in regions where the hydrological models are accurate. Ultimately, this will lend more weight to the validation of the passive microwave algorithms. Comprehensively validated algorithms should then be able to estimate SWE more accurately in areas of the world where the hydrological models are incapable of providing reliable estimates on account of sparse meteorological station networks. An even stronger reason for using snow hydrology models is through their combination with microwave emission models. Since the microwave emission signal from a snow pack is related in some way to the SWE, a snow energy or mass balance hydrology model can be used to ‘unravel’ the microwave signal and provide a better, more dynamic estimate of SWE or snow depth.

It appears, therefore, that good potential exists for estimating SWE or snow depth and characterizing their spatial variability using remote sensing and hydrological models of snow energy or mass balance dynamics. However, while these models are in development, there is a conspicuous lack of attention to validation frameworks of SWE or snow depth estimates. This statement is an important one and perhaps liberal in scope since energy balance models of snow have a strong tradition of rigorous validation. However, at the scale at which they have been applied, the validation is relatively straightforward. At local or regional scales, validation is less straightforward and has often been implemented in not the most robust of ways. Typically, most validation exercises to test passive microwave estimates have assumed that point measurements of SWE are ‘representative’ at the passive microwave support scale (grid sizes of 25 km × 25 km). In some regions of the world this may indeed be the case. However, passive microwave sub-grid scale heterogeneity of snow depth or SWE is an important issue that requires some formal attention; how can hydrologists use existing point measurements at the footprint scale? Simple comparisons between point measurements and areal estimates are often completely inappropriate, perhaps when the site location is in a region where land cover is highly variable or terrain steep and dissected and snow depth is highly variable; one point estimate of snow depth is unlikely to represent accurately the spatial footprint average. Furthermore, if we persist with the general approach of comparing point measurements of SWE with areal estimates from

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passive microwave models and algorithms, it is necessary to determine how many points are needed to adequately perform the validation. More specifically, what is the mechanism that determines the required density of snow measurement sites for a given accuracy requisite of passive microwave estimate and how might this density vary with changing SWE conditions or under different vegetation cover or terrain? This issue is an important one that requires attention. One potential solution to this problem is to examine the possibility of developing a more analytical approach to error propagation for the remote sensing of SWE and snow depth. There is a large literature on the characterization of error in spatial environmental modelling (e.g. Heuvelink, 1998). It would probably be of great interest to the remote sensing and snow hydrology community for a framework to be developed that could be universally adopted for validation studies in this field. A key challenge with such an approach is that all component variables in the algorithm, coupled model and ancillary data require associated error estimates. In the case of the coupled SNTHERM and DMRT approach, this would mean that for every variable used in the method, an error would need to be derived and combined in an analytical method (such as the Taylor expansion) to produce an overall estimation error statistic. This is quite some challenge since it is often very difficult to provide robust error quantities for many of the terms in SWE estimation algorithms or hybrid models described previously. However, the advantage of such an approach would be to make the estimates of SWE or snow depth highly attractive to many data users since for each estimate of SWE an error term would also be generated. Specifically, snow product users such as land surface modellers or climate modelling scientists who often require error estimates along with the actual variable estimate would find this error approach of great value.

In conclusion, then, there are various reasons why spatial models are used in the representation of snow depth or SWE at various spatial scales. Some of the outstanding issues concerning the estimation of SWE and snow depth will be addressed directly and indirectly in the near future thanks to several new technological and scientific developments in planning or under way. First, with the launch of Aqua and the availability of AMSR-E data in the near future, the spatial scale of observation of snow from space will be the most detailed ever. The potential to explore some of the spatial variability issues further will be greatly enhanced. Furthermore, with science field experiments such as the NASA Cold Lands Processes Experiment (CLPX), many of the questions regarding spatial variability and spatial representativity of snow properties from micro- to local scales of variation will be addressed (Cline *et al.*, 2002). This is an important experiment involving many teams of scientists undertaking laborious field experiments at the micro- and local scale. However, with these prospects, it might be possible to begin developing a framework for error estimation. Ultimately, the errors associated with snow depth and SWE estimation from spacecraft instruments and terrestrial models should be reduced thereby enhancing our ability to quantify the role of snow in the global hydrological cycle.

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